

Introduction

As part of the SIT4Energy project, we developed the Smart Energy Management Dashboard to support small energy providers (e.g. local or municipal utilities) to improve energy management as part of their energy planning tasks. Currently, there are several commercial applications to forecast energy demand and supply, however the majority consisted of black-box forecasting systems based on complex datasets. Usually, these applications provide accurate results, however, it is difficult to understand the results by people with non technical knowledge. For that reason, our application is focused on using explainable machine learning methods (e.g. kNN algorithm) to offer a solution to support utility analysts to improve their decision making, specially to manage better the growing number of prosumers in smart grids.

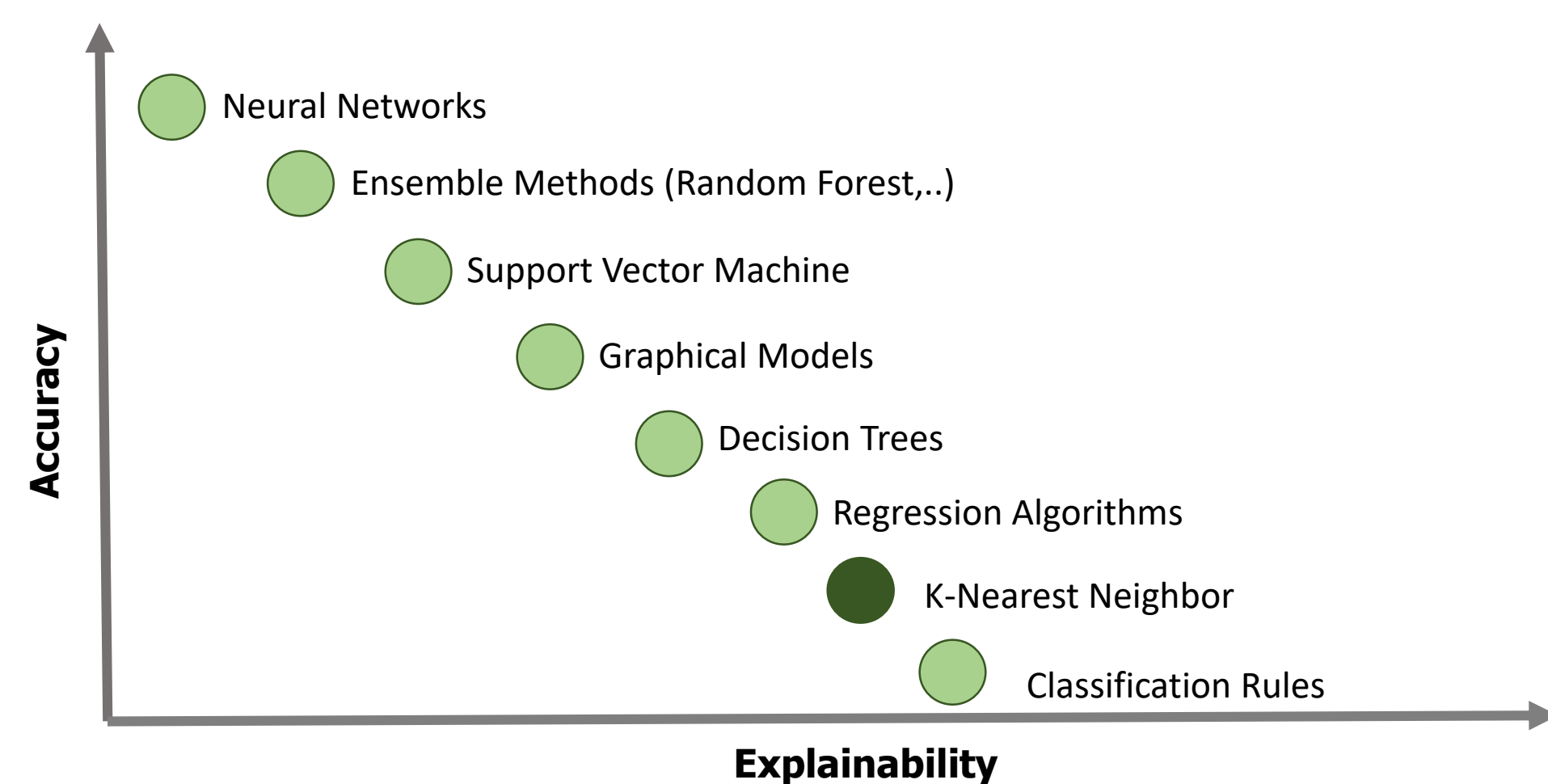


Figure 1: Comparison of forecasting methods based on accuracy and explainability

System design and implementation

The Smart Energy Management Dashboard is based on the idea of providing utility analysts with a tool that provides forecasts of electricity demand based on user-defined parameters. The combination of explainable machine learning and visual analytics techniques allows us to offer users an interactive solution to support their energy management activities. In order to produce the visualisations of the dashboard, we manage a MySQL database. The data is pre-processed by using a series of python scripts. In this way, the kNN algorithm uses it to produce the results. Finally, the results are prepared and presented in the dashboard as several visualisations created by using python libraries such as plotly and dash.

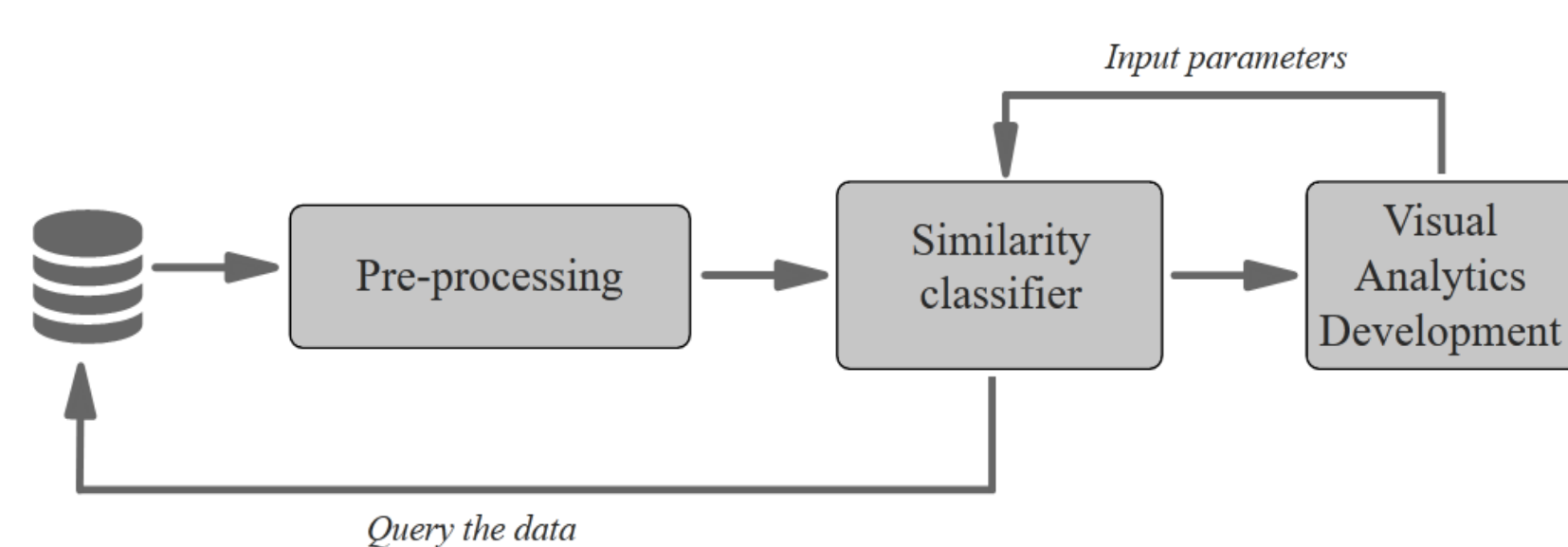


Figure 2: Smart Energy Management Dashboard Architecture

The Smart Energy Management Dashboard

The dashboard combines the result of the machine learning (kNN) with interactive visualizations to support utilities to understand the most likely forecast and identify relevant daily consumption patterns. To start, the dashboard presents weather parameters corresponding to the expected day ahead and also the k value (corresponding to the number of the most similar days to be presented in the dashboard), see Figure 3. Based on this input, the kNN algorithms identifies the k most similar days in the historical data and provides this information in the dashboard.

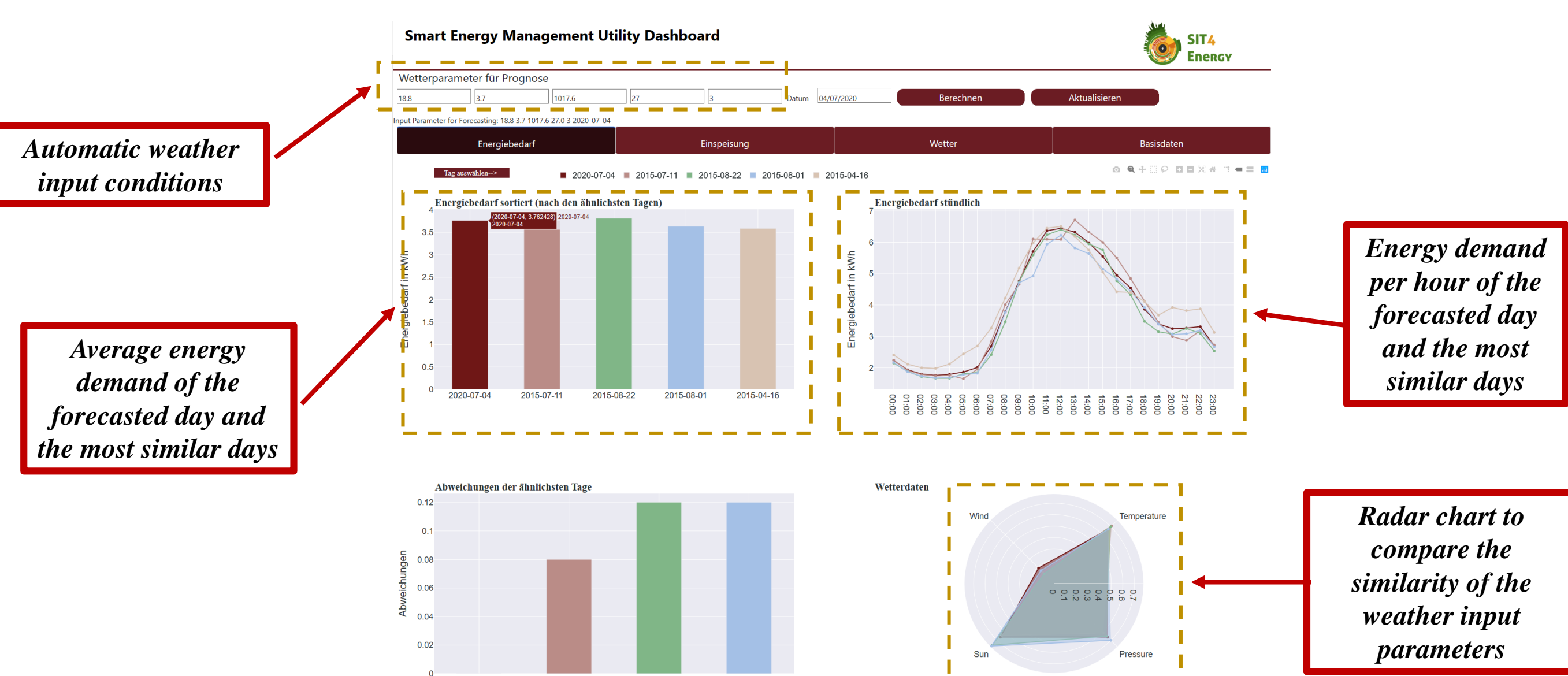


Figure 3: Forecast energy demand and the most similar days

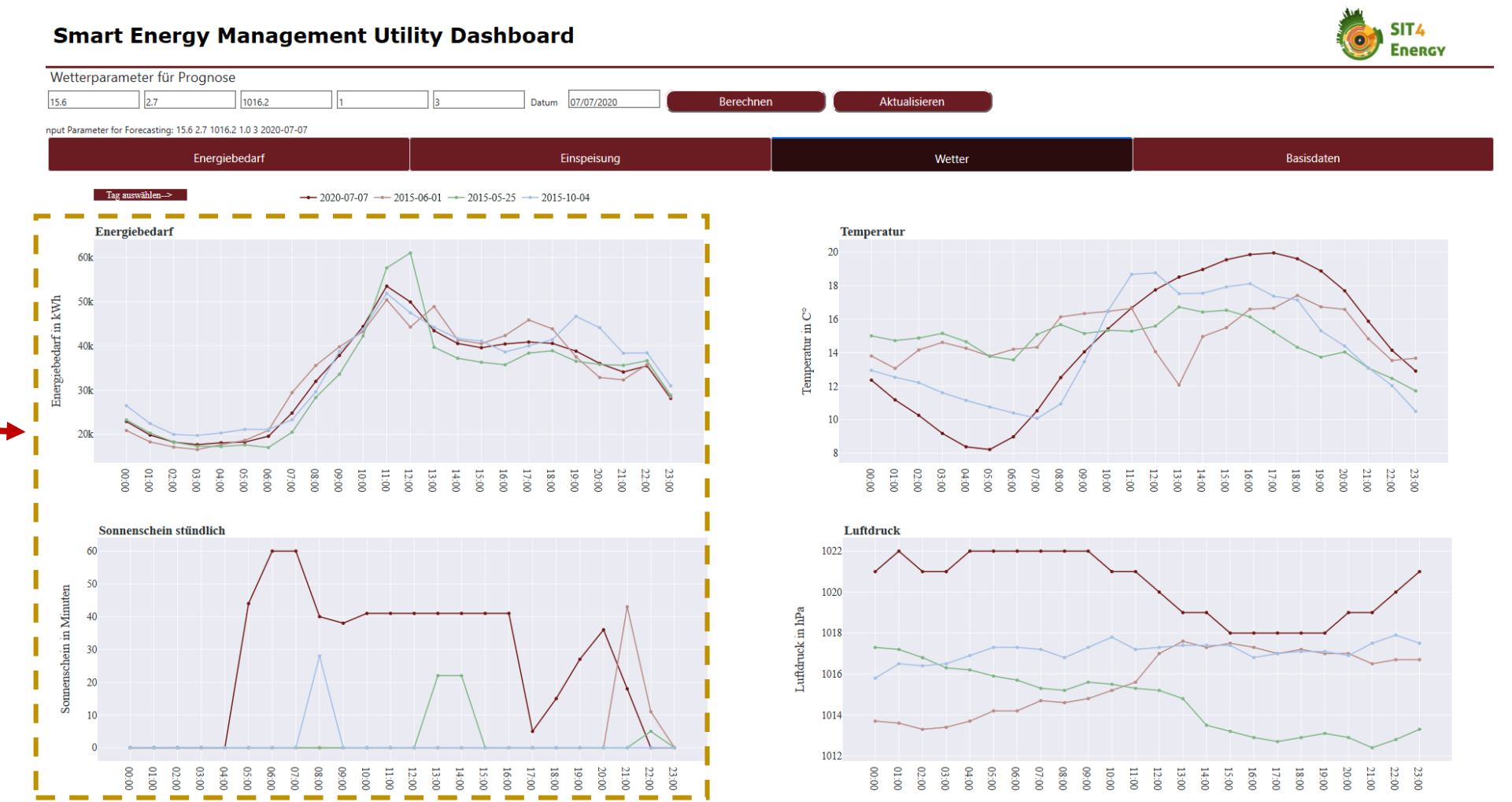


Figure 4: Forecast energy production and detailed weather data

The dashboard presents the forecasted consumption based on the average of the most similar days. The resulting data are visualized interactively in the dashboard to allow the user to inspect and analyse the results. By comparing characteristics of similarity between the days delivered by the kNN algorithm and the target day, the analyst can understand why the machine learning process considered those days as most similar – and to which extent and what parameters they indeed are similar, see Figure 1.

In addition, Figure 4 presents more detailed information such as weather (e.g. temperature, wind speed) to support the user to analysing and understanding the behaviour of the input factors in the dashboard and the impact on consumption.

Evaluation

We performed accuracy tests of the implemented kNN-based forecasting algorithm on a historical dataset covering one year (electricity consumption and production and weather data) to compare with different forecasting methods, see Table 1. Initial results of the kNN presents better results by calculating the average of the four closest neighbours (MAPE 5.06%). Despite the little higher difference compared with the results of different forecasting models, the explainability of the kNN could offer additional support to their users due to their limited technical knowledge about machine learning.

AI Algorithm	MAE (kWh)	MAPE (%)	Standard Deviation
kNN	2057.711	5.06	0.467
Decision Tree	1861.409	4.58	0.0034
Deep Learning	1967.011	4.80	0.0054
Generalized Linear Model	1893.497	4.61	0.0050
Gradient Boosted Tree	1378.596	3.33	0.0027
Random Forest Tree	1535.055	3.76	0.0032
Support Vector Machine	2104.956	5.24	0.0034

Table 1: Benchmarking comparison with other AI methods

kNN avg Neighbours	MAE (kWh)	MAPE (%)
2	2148.434	5.25
3	2263.809	5.56
4	2057.711	5.06
5	2200.683	5.46
6	2214.884	5.67
7	2296.973	5.55
8	2245.222	5.54
9	2246.998	5.54
10	2276.238	5.60

Table 2: Accuracy results of the avg 10 first neighbours

Future work

As future steps, we want to complement the accuracy evaluations by including additional datasets. In addition, we expect to consider additional parameters in the forecasting algorithm (e.g. holidays or working days) as well as to include explicit explanations to facilitate users to understand the process and in this way, to conduct additional evaluations to measure explainability, usability and therefore to improve the accuracy tests.

References

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Key facts

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Consortium Coordinator: Dr. Dimitros Tzovaras (CERTH)
Consortium: 4 partners from 2 countries
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The partners



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